Yet another look at mutual fund tournaments

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The dynamics of the impact of past performance on mutual fund flows

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Abstract

This paper documents a hump-shaped pattern in the sensitivity of mutual fund flows with respect to their past performance. More precisely, the sensitivity of fund flows to last quarter's performance is generally smaller than to performance two or three quarters ago. The sensitivity to performance in quarters even further in the past decreases monotonically. We attribute this finding to the presence of less sophisticated (non-professional) investors. These investors are especially attracted to funds with large marketing efforts and the hump-shaped pattern is indeed most pronounced for these funds. We find that only 68% of investors in funds with large marketing expenditures reacts immediately to new performance information, while for zero 12b1-fee funds this is 100%.

Keywords: 12b1-fee, Flow-performance relationship, Investor behavior, Marketing expenditure.

JEL Classification: G11.

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1 Introduction

Many studies have recently analyzed the determinants of the behavior of mutual fund investors, concentrating on the relation between net inflows to mutual funds and their past performance. This research is of obvious relevance for both mutual fund managers and their regulators. For the managers, it is important to know the factors that determine the total net assets under management which drive their compensation. The regulators should be aware of the incentives for risk-taking induced to managers by the existing investor behavior patterns.

The stylized findings indicate a clear positive impact of risk-adjusted as well as raw past performance on subsequent net inflows (see, e.g., Ippolito, 1992, and Gruber, 1996). The relationship appears convex, indicating that most of the inflows are attracted by the best performing funds (see, e.g., Chevalier and Ellison, 1997, and Sirri and Tufano, 1998). Flows are also directly related to fund visibility, as funds belonging to larger families (see Sirri and Tufano, 1998) and funds advertising in the financial magazines (see Jain and Wu, 2000) tend to attract larger flows. Also, Del Guercio and Tkac (2001) document a significant "Morningstar star effect" on fund flows. Moreover, flows into a fund are found to be positively related to the performance of the fund family, measured, e.g., as average performance within the family (see, e.g., Ivkovic, 2000) or through the presence of star performers in the family (see, e.g., Nanda, Wang, and Zheng, 2004). Khorana and Servaes (2003) document that families with above average fees, gain market share as they lower their fees. Barber, Odean, and Zheng (2002) find that fund flows are more sensitive to the salient fees such as loads and commissions than to operating expenses. Finally, Del Guercio and Tkac (2002) document that mutual fund investors use less sophisticated measures of fund performance than pension fund clients. Our findings below are consistent with these latter results.

The findings on the flow-performance relationship can be related to the literature on performance persistence of mutual funds (see Hendricks, Patel, and Zeckhauser, 1993, Wermers, 2000, Baks, Metrick, and Wachter, 2001, and many others). Overall, these studies find strong evidence of persistence among bad performers and mixed evidence for consistent superior persistence. Assuming rational investor behavior, this implies that the relationship between fund flows and past performance should be the strongest among the worst-performing funds, which is opposite to the observed pattern (see Sirri and Tufano, 1998). This difference can be explained by a number of institutional and psychological factors, which prevent large outflows from funds with bad past performance. Market frictions such as the presence of search costs, back-end load charges, tax considerations, and restrictions of the investment retirement plans increase the transaction costs of withdrawing money from the poorly performing funds, while the status-quo bias (see Zeckhauser, Patel, and Hendricks, 1993) and the cognitive dissonance bias (see Goetzmann and Peles, 1997) make investors ignore information about bad fund performance.

The present paper argues that, in addition to the above findings, there exists a clear hump-shaped pattern in the dynamic structure of the influence of past performance on mutual fund inflows. The flow-performance sensitivity is not constant as previous studies implicitly assume. We show that the sensitivity of inflows with respect to very recent (up to the first three quarters) performance is increasing with the lag, after which the sensitivity monotonically decreases. Consequently, performance six months ago has a larger impact on current inflows than performance over the last month. For lags beyond three quarters, the sensitivity slowly decreases with the lag. We attribute this empirical pattern to the existence of an information dissemination lag, which is to say that some investors do not react immediately to new performance information. This explanation is substantiated by our finding that the hump-shaped pattern is most pronounced for funds with high marketing expenditures as measured by the dollar 12b1-fee, i.e., the percentage 12b1 fee multiplied with total assets under management. Our explanation is that those high 12b1-fee funds primarily target small and less sophisticated investors that do not follow performance information closely and thus react with a delay of, apparently, up to nine months. More sophisticated (institutional) investors might prefer funds with smaller 12b1-fees and for these low 12b1-fee funds, we indeed find an essentially monotonically decreasing sensitivity pattern.

A second finding is that young funds are more sensitive to performance up to three years ago than old funds, but equally sensitive to performance more than three years ago. The implied overall lower flow-performance sensitivity for older funds is in line with Chevalier and Ellison (1997), but we identify it as pertaining to the most recent performance of up to three years only. A possible explanation for this effect is that investors are more lenient towards relatively bad performance of young funds around their date of inception. In such a situation, flows into young funds will indeed be more sensitive to recent past performance than flows into older funds are sensitive to such more recent performance. Finally, as is to be expected, we do not find any evidence for an information dissemination lag for index funds. We have investigated possible differences in the information dissemination lag for various categories of funds, but these are not present in our data in any significant way.

The structure of the paper is as follows. Section 2 describes the CRSP mutual fund data that we use. It also gives a parametric estimate of the dynamic structure of the influence on past performance on fund flows. From this estimate, the information dissemination lag is already visible. To substantiate our claims, we introduce in Section 3 a more structural model for the way different groups of investors react to past performance information. This section also contains our main empirical findings. Section 4 subsequently contains some robustness results concerning index funds and funds with different investment objectives. Finally, Section 5 concludes.

2 Data and methodology

The data employed in our analysis come the from CRSP Survivor-Bias Free Mutual Fund Database[1]. In line with other studies, we concentrate on the sample of diversified US equity funds.[2] Our sample period is January 1991 to December 2001, for which we have monthly data on fund flows. The data also include starting date, monthly returns, and other fund characteristics, such as front load, expense ratio, 12b-1 fee, and family identifier. These latter variables are available on an annual frequency only.[3] Since we use up to a five-year horizon for fund performance, our analysis is restricted to the funds which have at least five years of the return history available. Thus, the term "young funds" below refers to funds which exist for little more than five years. We have annualized monthly returns and flows in order to make our results comparable to existing evidence, which is generally based on annual data. The number of funds in the sample grew from 383 in 1991 to 1826 in 2001, and we have 109513 fund-month observations in total.

Table 1 presents descriptive statistics for the funds in our dataset. During the sample period, an average fund had a sixteen-year performance record, controlled over \$1.2 billion of assets, and experienced an inflow (as defined below) of 1.4% per year. The cross-sectional variation in flows was quite large, ranging from an average 53% outflow for the bottom quintile to 68% inflow for the top quintile. This may be partly attributed to the high returns (about 15% per year) and volatility (about 19% per year) prevailing during the 1991–2001 sample period. On average, funds charged 1.9% front load and adopted a 1.3% expense ratio, including 0.24% 12b-1 fee (around \$2.1 million in absolute terms). An average fund family comprised of seven funds and had about \$3.8 billion of assets under control.

In line with the literature (see, e.g., Gruber, 1996), net relative flows are defined as a net percentage growth of fund assets via

$$f_{i,t} = \frac{TNA_{i,t} - (1 + R_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{2.1}$$

where $TNA_{i,t}$ denotes fund i's total net assets at the end of month t and $R_{i,t}$ is return of fund i in month t. This definition is based on an assumption that all investor earnings are automatically reinvested in the fund and flows occur at the end of month t. Due to the low autocorrelation in monthly returns, flows occurring at other instances during the month will not bias any of our results.

[1]Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago [2002]. Used with permission. All rights reserved. www.crsp.uchicago.edu.

[2]We select funds that have either ICDI objective "Aggressive Growth", "Growth and Income", or "Long-Term Growth"; or Strategic Insight objective "Aggressive Growth", "Growth & Income", "Growth", "Income Growth", "Growth MidCap", or " Small Company Growth". When both ICDI and Strategic Insight objective codes were missing, we selected funds with Wiesenberger objective "Growth and Current Income", "Long-Term Growth", "Maximum Capital Gains", or "Small Capitalization Growth".

[3]In our regressions of monthly flows, we used annual fund characteristics as of the last calendar year. When these were missing, we substituted them with the value of the corresponding fund characteristic from the previous or, if that was unavailable, from the following year.

To curb the influence of outliers on the coefficient estimates, we winsorize net relative flows (a dependent variable in our regressions) at the 0.5th and 99.5th percentiles.[4] In order to avoid the impact of mergers, we exclude from our data set observations of funds which merged during a given month.

As mentioned in the introduction, the focus of the present paper is on the dynamic pattern of the influence of past performance on mutual fund flows with the aim of identifying possible differences in information dissemination. Almost all studies referred to in the introduction analyze flows at the annual frequency, identifying in fact the average flow-performance sensitivity over several years of past performance. Accordingly, the standard model in this literature specifies net relative flows as a linear function of past performance and a set of control variables, i.e.,

$$f_{i,t} = \alpha_0 + \alpha_1 \tilde{r}_{i,t-1} + \alpha_2^T x_{i,t-1} + \varepsilon_{i,t}, \tag{2.2}$$

where $\tilde{r}_{i,t-1}$ is some measure of fund i's performance up to period $t-1$. The vector $x_{i,t-1}$ includes control variables such as fund size, age, fees, riskiness, and aggregate inflow into the category the fund belongs to. Previous studies use various choices for measuring a fund's past performance (raw returns, risk adjusted returns, Jensen's alpha, ...), but do not explicitly acknowledge the fact that investors may differ with respect to the actual period of past returns that is used to assess past performance. Such different investors could lead, for *aggregate* flows into funds that we study, to different monthly returns in the past having different effects on the current month's inflow. In the next section, we discuss this aggregation and its consequences in more detail, but in the present section we model it, for simplicity, by taking the performance measure $\tilde{r}_{i,t}$ as a parametrically specified weighted average of risk-adjusted returns over the past sixty months.

More precisely, we define risk-adjusted returns on the basis of a four-factor model with the market, size, book-to-market, and one-year momentum factors, as in Carhart (1997)[5], i.e.,

$$RAR_{i,t} := R_{i,t} - R_t^f - \sum_{k=1}^{4} \hat{\beta}_i^{(k)} F_t^{(k)}, \tag{2.3}$$

where $F_t = (R_t^{(m)} - R_t^{(f)}, SMB_t, HML_t, MOM_t)$ denotes the vector of the market return in excess of the risk free rate, the excess return on the size portfolio, the excess return on the book-to-market portfolio, and the excess return on the momentum portfolio. The factor loadings $\beta_i^{(1)}, ..., \beta_i^{(4)}$ are estimated using all observations available for a given fund. Average factor loadings presented in Table 1 are in line with the literature. The table also presents the resulting average Jensen's alpha. We performed the analysis below using raw returns instead of the risk-adjusted returns (2.3), as well, which yielded similar conclusions.

[4] A similar approach was used in Barber, Odean, and Zheng (2002). Alternative approaches include using a truncated regression and excluding small funds, say, with TNA below $20 million (see, e.g., Sirri and Tufano, 1998). Our results are qualitatively the same irrespective of the method used.

[5] We thank Kenneth R. French for the opportunity to use the factor returns provided at his website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Measuring a fund's past performance by, say, a five-year Jensen's alpha for the purpose of predicting aggregate fund inflows, implicitly assumes that past performance in all past sixty months is equally important for predicting fund flows. In line with the arguments given above, we study possibly different influences of performance in given months by measuring fund i's performance as

$$\tilde{r}_{i,t} = \sum_{j=1}^{60} w_j RAR_{i,t-j}, \tag{2.4}$$

for some weights $w_1, \ldots, w_{60}$. Note that we are concerned with flows at the aggregate level of a fund, i.e., we do not have information available of flows into funds for individual (groups of) investors. Therefore, the weights in (2.4) can be non-constant due to the fact that individual investors weigh past returns with lag-dependent weights, due to the fact that various groups of investors have different fixed-weight performance measures, or due to a combination of both. We elaborate on this point in Section 3, where we provide a more structural model for the weights $w_1, \ldots, w_60$.

If the performance coefficients $w_1, \ldots, w_{60}$ are unrestricted in the specification (2.4), the estimates can be very noisy. To mitigate this effect, we impose in the present section a polynomial structure for these performance coefficients. The polynomial structure allows for constant, monotonically decreasing, and quasi-concave functional forms. More precisely, the present section imposes a fifth-order polynomial structure for the coefficients $w_1, \ldots, w_{60}$, i.e.,

$$w_j = \sum_{p=0}^{5} \theta_p p! j^{-p}, \text{ for } j = 1, ..., 60. \tag{2.5}$$

The empirical results indicate that a polynomial of order five suffices. In order to identify the overall performance sensitivity parameter α_1 in (2.2), we normalize the weights w_j, so that the average of the performance coefficients is equal to one: $\sum_{j=1}^{60} w_j/60 = 1$. If all weights are equal to each other (i.e., $\theta_p = 0$, $p = 1, \ldots, 5$), the weighted sum of risk-adjusted returns in (2.4) equals Jensen's alpha estimated over a sixty month period.

From an empirical point of view, one should keep in mind that small funds have extreme relative flows that could dominate OLS estimates. Unless heteroscedasticity-consistent standard errors are computed, inference based on OLS estimates will be biased. For efficiency reasons, we model the variance of the error term and compute weighted least squares estimates. Throughout the paper, the variance of $\varepsilon_{i,t}$ is modelled as

$$\mathrm{Var}(\varepsilon_{i,t}) = \exp\left(\delta^T x_{i,t-1}\right), \tag{2.6}$$

with $x_{i,t-1}$ denoting the same control variables as are being used in the regression (2.2). This specification reflects that the disturbances are heteroscedastic, in contrast to what is often assumed in the literature. In line with standard econometric techniques, the coefficients δ are estimated on the basis of OLS residuals.

The estimation results of the flow-performance relationship (2.2) with performance measure (2.4) with dynamic coefficients (2.5) are in Table 2. For brevity, this table only presents the estimates for the control variables we use throughout. Since these coefficients are close to the estimates in the next section, they will not be discussed here. The focus of interest in the present paper is the resulting lag structure of the influence of past performance on mutual fund flows. For the polynomial structure imposed in the present section, the structure is given in Figure 5.1. The upper and lower lines in Figure 5.2 give 95% pointwise confidence bands. In line with the literature, we find a clearly positive effect of past performance on current fund flows. Also, Figure 5.1 shows that the flow-performance sensitivity seems to be monotonically decreasing in the lag for performance more than half a year ago. Although this is in part enforced by the imposed polynomial structure, this effect is robust for more flexible specifications as we will see in the next section. More importantly, there seems to be an indication that performance over the very last month is less important than performance, say, six months ago. In Section 3 we relate this empirical finding to performance information dissemination. We argue that less sophisticated investors react with a certain lag to performance information, because they follow the market less intensively. As we do not have information available about flows for individual mutual fund investors, we substantiate this claim by showing that the information dissemination lag is especially pronounced for funds with high marketing expenditures, that we expect to attract mostly less sophisticated investors.

3 Information dissemination in the mutual fund industry

The focus of the present paper is to identify possible causes of the flow-performance relation pattern for recent months as documented in the previous section. We assume that, when making investment decisions, an investor takes into account fund performance over some period in the past. Two effects play a role. First of all, less sophisticated investors may follow the mutual fund market less intensively and thus might react to performance information with a certain lag. Secondly, investors may differ with respect to the length of the period in the past that is used to determine past performance. More precisely, investors may take average performance into account over, say, one up to four years. When investors are more lenient toward young funds concerning past performance around their date of birth, flows into young funds will be determined on the basis of a shorter evaluation period.

To accommodate both effects, we assume that different groups of investors base their investment decision on past performance of mutual funds measured over a period of either $p = 12$, 24, 36, or 48 months in the past and starting with an information dissemination lag of either $l = 1$, 3, 6, or 12 months. More precisely, we assume that for each given group of investors, the performance relevant for their investment decision is measured by (2.4) with

$$w_j = \begin{cases} 0 & , \quad j = 1, \ldots, l-1, \\ 1 & , \quad j = l, l+1, \ldots, l-1+12p, \\ 0 & , \quad j \geq l+12p, \end{cases} \tag{3.1}$$

for some lag $l = 1$, 3, 6, or 12 months and some performance horizon $p = 1$, 2, 3, or 4 years. Clearly, aggregating the flow-performance relationship as implied by the weights (3.1) for all investors, gives an overall flow-performance relationship which is also of the form (2.4), but now with each w_j proportional to the fraction of investors (as measured by total wealth) that takes month $-j$'s return into account when making the investment decision. Of course, it may be that also individual groups of investors weigh performance in the past differently for different months. In that case, investors use past performance measure which are not of the form (2.4) with weights (3.1). However, since our data contain only aggregate (over all investors) inflows, such an effect cannot be identified in the present paper. Moreover, since the resulting dynamic pattern of the overall flow-performance relationship is specified with a large number of parameters ($l = 1, 4, 6, 12$ and $p = 1, \ldots, 4$ makes 16 degrees of freedom), these estimates are generally noisy. Assuming some smoothness of the overall flow-performance sensitivity pattern, we resolve this issue by presenting weights w_j that are smoothed by taking the average estimate for the nearest five lags, i.e., $(w_{j-2} + w_{j-1} + w_j + w_{j+1} + w_{j+2})/5$. For lag $j = 1$, we present w_1, while for lag $j = 2$, we take the average of $w_1, \ldots, w_3$. We proceed in a similar manner at the far end of our lag spectrum, i.e., for $j = 59$ and $j = 60$.

The resulting dynamic flow-performance pattern for the model (2.2), with performance measure (2.4) is given in Figure 5.2, while the estimated effects of the control variables $x_{i,t}$ are given in Table 2. The information dissemination lag shows once more as the flow-performance sensitivity increases for about the first three to five month lags and decreases for the remaining lags. However, given the confidence bands, these effects are not statistically significant. More precisely, the p-value for testing that last month's performance is equally important as performance six months ago is 0.54. We will see below that this effect is strongly significant for high 12b1 funds, while absent for low 12b1 funds. As the analysis underlying Figure 5.2 does not allow for interaction of the flow-performance pattern with marketing expenditures of funds, we find, on average, a non-significant effect.

The parameter estimates in the middle column of Table 2 show that larger and older funds have, ceteris paribus, smaller (relative) inflows. This is in line with the findings in, e.g., Sirri and Tufano (1998), but also with Chen et al. (2003). That paper documents that larger and older funds generally perform worse than average funds, which in turn leads to smaller inflows. Concentrating on the statistically significant estimates we see that both 12b1-fee and non-12b1-fee have a positive effect on fund flows. Barber, Odean, and Zheng (2002) document a positive effect of operating expenses (in particular 12b1 fees) on fund flows as well. However, they find a significantly negative effect of the load fee on fund flows, while we find an insignificantly positive effect. Also note that we consider the logarithm of the dollar 12b1-fee, which is obtained by multiplied the % 12b1-fee with Total Net Assets. We do this to capture the effect that, for our purposes, the *amount* of dollars available for marketing influences flows. From the estimates in the middle column in Table 2 we find that doubling the 12b1-fee to increase marketing expenditures will increase, ceteris paribus, relative inflows with $1.50 \times \log(2) = 1\%$. More funds in a given family leads to smaller inflows in line with Nanda, Wang, and Zheng (2004). We find that a fund belonging to a larger and older family attracts larger inflows. Interestingly, Chen et al. (2003) indeed find that large family size does not erode performance, however Ivkovic (2000) documents a negative effect of family age on family flows. As is to be expected and in line with the literature, larger flows into the category the fund belongs to, lead to larger flows into the individual fund as well.

In order to substantiate our claim that the information dissemination lag is primarily caused by less sophisticated investors, which may be expected to follow the mutual fund market less intensively, we assume that these investors are especially sensitive to marketing efforts of individual funds. In that case, one might expect the flow-performance sensitivity pattern as documented in Figure 5.2 to be different for funds with different 12b1-fees and/or age. In order to study this effect, we interact the flow-performance sensitivity coefficients w_j in (2.4) with the log dollar 12b1-fee and the log age of the fund. The effects of the control variables are in the rightmost column of Table 2. These results are qualitatively the same as before. The interaction effects are clearly significant as the p-value of the hypothesis that they are jointly zero equals 0.000 for the interaction with age and 0.099 for the interaction with the dollar 12b1-fee.

Figure 5.3 shows the flow-performance sensitivity pattern for an average fund, for high and low 12b1 funds, and for young and old funds. The graph for the average fund follows that in Figure 5.2. The graph for high 12b1 funds is based on a fund with average fund characteristics as presented in Table 1, however, with marketing expenditures as measured by the dollar 12b1 fee equal to the average in the upper quintile with respect to this variable, i.e., \$10.01 million instead of \$2.11 million. The graphs for low 12b1 funds and young and old funds are constructed similarly. From Figure 5.3 it is clear that flows into high 12b1 funds are more sensitive to past performance than for an average fund. This is in line with Jain and Wu (2000) and with Barber, Odean and Zheng (2002). Also, the increase in flow-performance sensitivity for recent months is most pronounced for these high 12b1 funds. The p-value for the hypothesis that the sensitivity to last month's performance equals that of six months ago for a high 12b1-fee fund is 0.015. As mentioned before, we explain this from high 12b1 funds attracting especially less sophisticated investors. In line with this explanation, for low 12b1 funds this effect can not be identified from our data (p-value of 0.772).

Figure 5.3 also shows some information dissemination lag for older funds. However, these older funds also tend to be the funds with larger marketing expenditures. More precisely, funds in the bottom age quintile have an average total 12b1-fee income of \$1.4 million, while in the top age quintile this is \$3.3 million. As mentioned above, the effect of age on the flow-performance sensitivity pattern does come out significantly in our analysis. From Figure 5.3, we see that for recent lags young funds are more sensitive to performance than old funds, while as of a lag of about three years they are equally sensitive. A possible explanation for this results is that investors are more lenient towards information about bad performance over the period right after the start-up of the fund. Such a behavior would lead to investors basing their investment decision for young funds on a shorter history of past performance, which in turn results in the flow-performance sensitivity patterns as documented.

The estimation results underlying Figure 5.3 also provide information on the (wealth weighted) percentage of investors that react with a certain lag. These estimated percentages and their standard errors are presented in Table 3. For an average fund, about 77% of the investors reacts immediately to new performance information. However, consistent with our explanations above, for investors attracted to high 12b1-fee funds this is only 68%, while all young fund investors react immediately to new performance information. This latter difference is also statistically significant as the induced confidence bands do not overlap. It is important to note that, even when investors react immediately to new performance information, this does not mean that the only take the very recent performance into account. More precisely, according to (3.1) they consider performance over a horizon of 12, 24, 36, or 48 months.

4 Robustness studies

Two obvious questions concerning the information dissemination lag come to mind. First of all, one may expect the information dissemination effect to be absent for index funds, as these do not propagate active management. Given the small number of available index funds (about fifty maximum at any point in time), we only considered estimation of the flow-performance sensitivity pattern using the fifth-order polynomial weights as in (2.5). The estimation results in Table 4 show that no significant dynamic pattern can be obtained, as all the polynomial coefficients are estimated very imprecisely (all t-statistics are well below 1.0). The resulting lag pattern is relatively noisy without any clear structure.

Secondly, one may wonder whether the observed patterns vary across funds with different objectives. Here as well, care has to be taken given the number of available funds for each investment objective category. We present in Figure 5.4 the results for the following combinations of Strategic Insight categories: (i) aggressive growth and small company growth, (ii) growth and growth midcap, and (iii) growth/income and income. The results are qualitatively the same for all three investment categories. One may observe a longer estimated information dissemination lag for the growth/income and income category, but this effect is not significant. Moreover, no information dissemination lag can be identified for the growth and growth midcap category. Again, we could not estimate the interaction with fee and fund age to any reasonable precision due to the small number of observations in the separate categories.

5 Summary and concluding remarks

The present paper documents that less sophisticated investors, as defined as investors attracted to highly marketed mutual funds, react with a lag of up to six to nine months before taking new performance information into account in their investment decision. This information dissemination lag is significant for high 12b1-fee funds, but not for low 12b1 funds or for index funds. We do not find that it differs significantly for various style categories. Alternatively, our results show that about 77% of overall mutual fund investors reacts immediately to new performance information while for highly marketed funds this is only 68%. At the same time, we also document that young funds are more sensitive to performance up to three years in the past than old funds, while for longer lags there is no significant performance sensitivity difference. One explanation for this latter effect is that investors are more lenient towards bad performance of funds around their date of inception when they have shown an improvement afterwards.

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	Overall		Bottom quintile		Top quintile	
Variable	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
Flow (%)	1.40	53.25	-53.22	43.91	67.95	65.50
TNA ($mln)	1245.86	4109.72	19.76	12.95	5240.45	8024.30
Age (years)	15.87	13.77	5.77	0.45	38.51	14.00
Front Load (%)	1.86	2.51	0.00	0.00	5.79	0.67
Expense Ratio (%)	1.30	0.85	0.63	0.21	2.23	1.36
% 12b1-fee (%)	0.24	0.33	0.00	0.00	0.81	0.18
$ 12b1-fee ($mln)	2.11	8.44	0.00	0.00	10.01	16.71
Family size (#)	7.23	12.11	1.00	0.00	25.62	17.13
Family TNA ($mln)	3820.01	19503.12	8.04	5.46	17886.49	40950.25
Family age (years)	16.39	17.30	3.06	1.45	46.58	14.36
Category Flow (%)	7.47	6.95	-0.89	2.88	16.82	3.74
Total risk (%)	19.49	10.35	9.21	2.29	34.31	12.05
Total return (%)	15.25	4.58	9.21	3.65	21.33	2.72
Alpha (%)	-0.82	4.09	-6.10	3.77	4.36	2.72
Beta Market	0.98	0.16	0.77	0.15	1.17	0.08
Beta SMB	0.20	0.36	-0.20	0.09	0.78	0.18
Beta HML	-0.01	0.33	-0.50	0.19	0.41	0.12
Beta MOM	0.02	0.18	-0.20	0.09	0.29	0.11

Table 1: Summary statistics for the CRSP Mutual Fund data set for the period January 1991 – December 2001. The units of measurement for the variables are added in parentheses. If applicable, the variables are annualized. Bottom and top quintile refer to calculations based on those funds with the smallest respectively largest 20% values for the variable at hand. The $ 12b1-fee is obtained by multiplying the % 12b1 fee with Total Net Assets (TNA).

	Polynomial		Structural without interaction		Structural with interaction	
Coefficient	Estimate	t-value	Estimate	t-value	Estimate	t-value
Constant	-15.13	-6.72	-14.23	-6.14	-12.15	-5.20
Log fund size	-1.12	-3.89	-1.31	-4.84	-1.42	-5.72
Log fund age	-3.40	-9.19	-3.52	-9.99	-3.80	-6.46
Front load	0.27	1.90	0.25	1.73	0.27	1.93
$ 12b1-fee	1.62	5.26	1.50	4.87	1.27	3.20
Non 12b1-fee	4.19	8.10	4.50	8.02	3.53	7.91
Fund risk	0.07	1.06	-0.02	-0.28	-0.05	-0.82
Funds in family	-1.77	-6.79	-1.80	-7.02	-2.00	-7.46
Log family size	1.89	7.19	1.88	7.27	2.18	9.74
Log family age	1.95	3.08	2.11	3.23	1.52	2.35
Category flow	0.29	4.86	0.25	4.43	0.24	4.33
R^2	0.13		0.15		0.19	

Table 2: Estimation results for the flow-performance relationship (2.2) for various specifications of the dynamic lag-pattern. The column "Polynomial" uses the fifth-order polynomial specification (2.5). The columns "Structural" refer to the flexible specification based on (3.1). The column "Structural with interaction" refers to this specification where age and dollar 12b1-fee may affect the dynamic flow-performance pattern. The parameter estimates for the lag pattern are not presented for brevity and are available upon request from the authors.

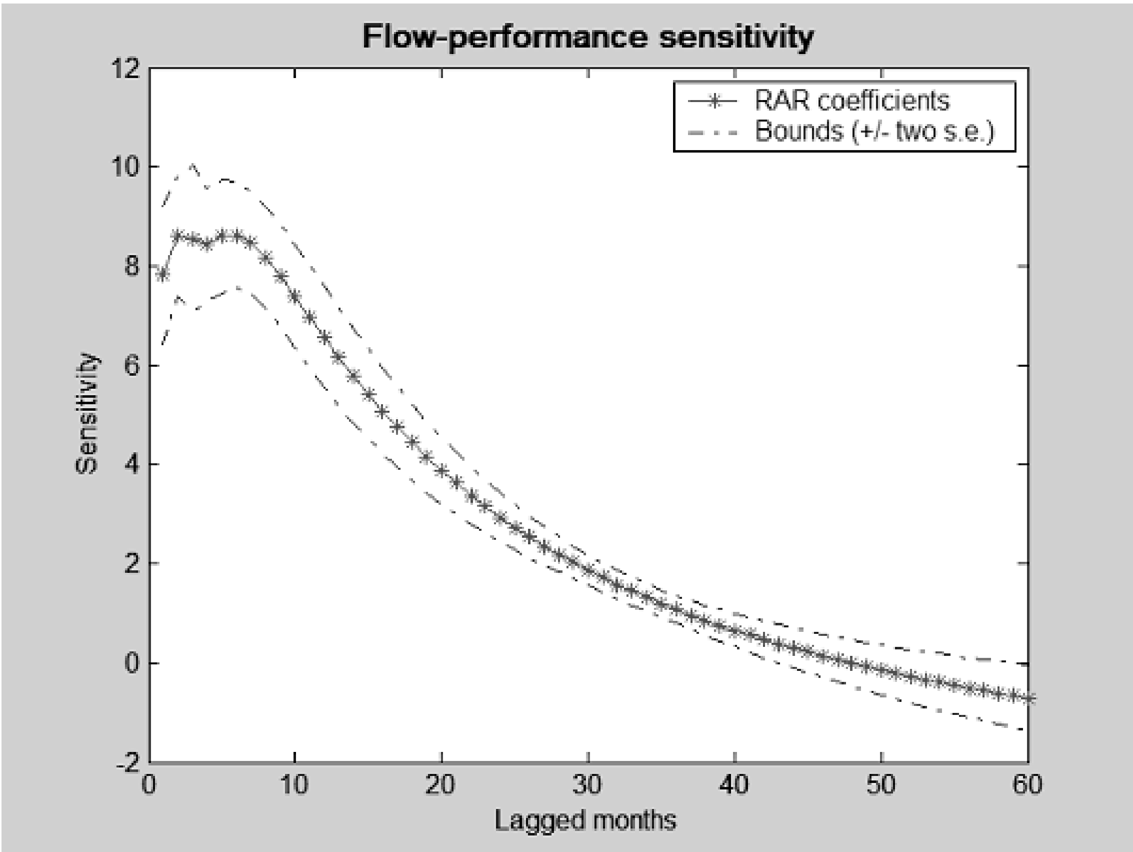

Figure 5.1: Dynamic structure flow-performance relationship with fifth-order polynomial performance coefficients.

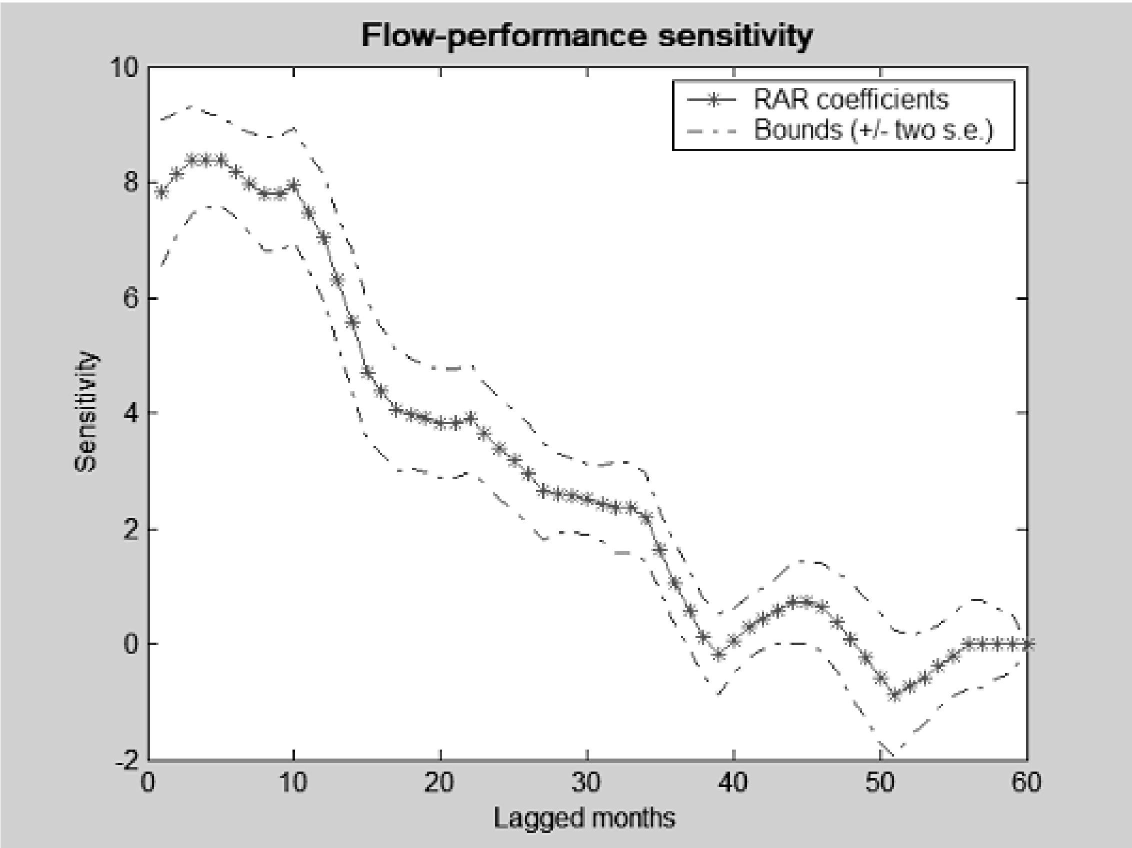

Figure 5.2: Nonparametric estimate dynamic flow-performance relationship; average over all funds. The upper and lower lines given 95% pointwise confidence bands.

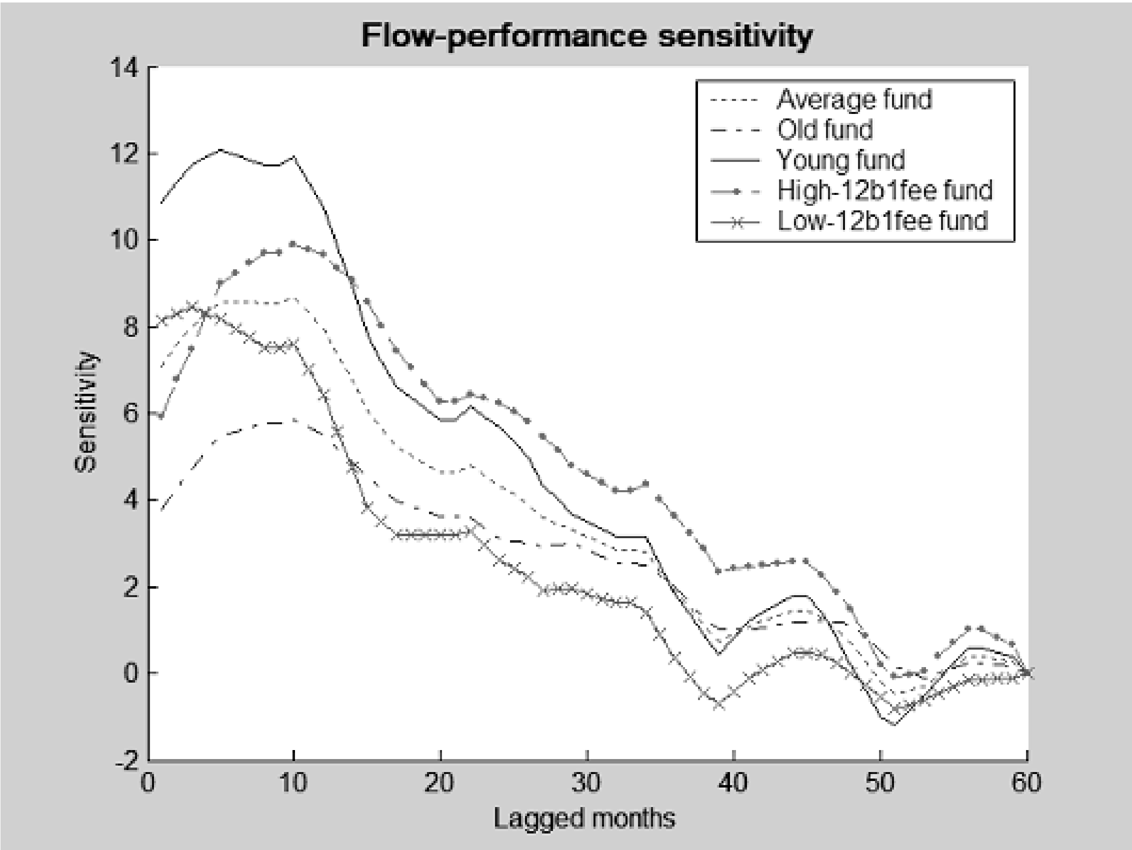

Figure 5.3: Nonparametric estimate dynamic flow-performance relationship for various funds. Graphs are for funds which are average in all dimensions, however, high and low refer to funds with for that variable are in the upper and lower quintile, respectively.

Lag	Average		High 12b1		Low 12b1	
1	77%	(9%)	68%	(11%)	104%	(8%)
3	16%	(7%)	18%	(10%)	4%	(7%)
6	-1%	(10%)	4%	(14%)	-15%	(7%)
12	7%	(12%)	10%	(15%)	7%	(11%)

Table 3: Estimated (wealth weighted) percentage of investors with a given dissemination lag for an average fund, a fund with 12b1-fee in the upper quintile of the distribution, and a fund with 12b1-fee in the lower quintile. Standard errors are in parentheses.

Coefficient	Estimate	t-value
Constant	-24.79	-1.69
Log fund size	-3.03	-2.44
Log fund age	-6.60	-2.13
Front load	0.56	0.91
$ 12b1-fee	65.87	2.73
Non 12b1-fee	1.15	0.20
Fund risk	-0.26	-0.36
Funds in family	0.46	0.27
Log family size	2.94	2.24
Log family age	2.49	1.03
Category flow	0.33	0.24
θ_0	-6.68	-0.46
θ_1	588.81	0.79
θ_2	-2855.26	-0.63
θ_3	3077.53	0.47
θ_4	-949.40	-0.34
θ_5	78.53	0.27

Table 4: Estimation results flow-performance relationship (2.2) with fifth-order polynomials performance coefficients for index funds only.

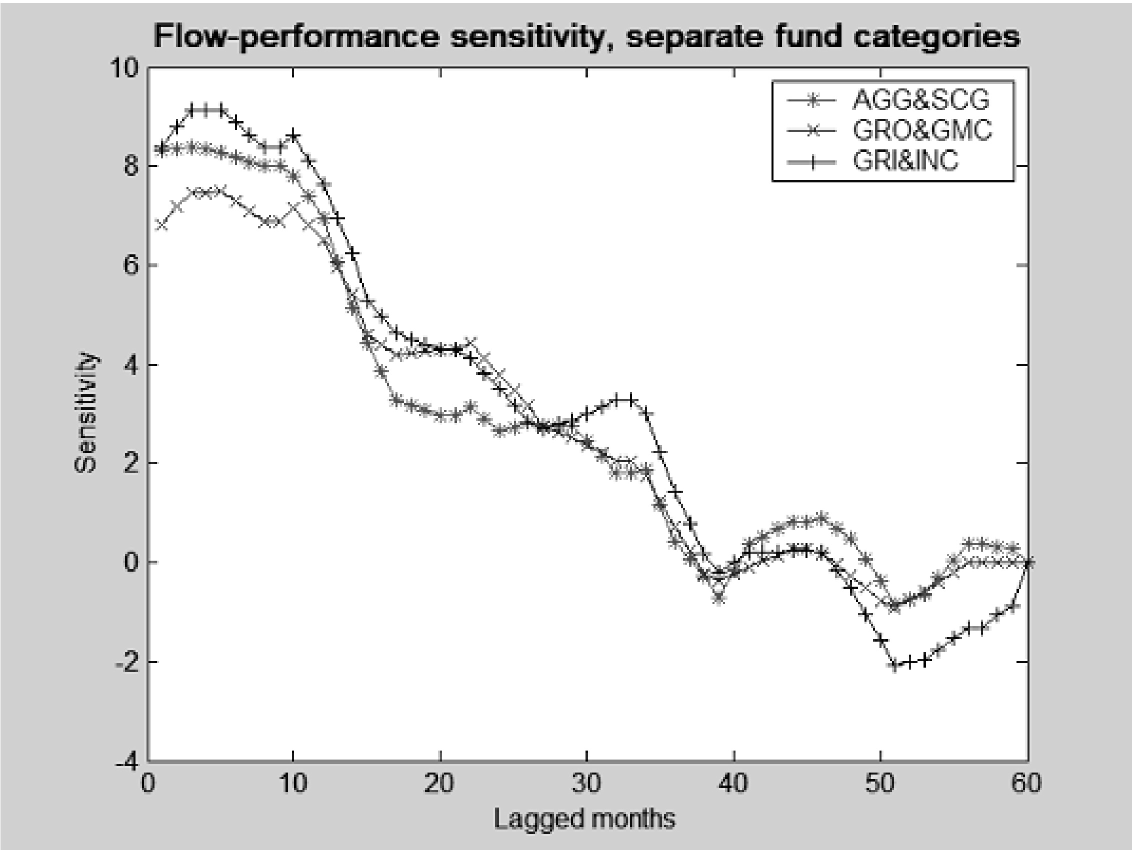

Figure 5.4: Nonparametric estimate dynamic flow-performance relationship for various categories of funds. AGG & SCG refers to the "aggressive growth" and "small company growth" category, GRO & GMC refers to "growth" and "growth midcap" funds, finally, GRI & INC refers to the "growth/income" and "income" category.